

An efficient parallel algorithm for $O(N^2)$ direct summation method and its variations on distributed-memory parallel machines

Junichiro Makino

*Department of Astronomy,
School of Science, University of Tokyo,
7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan.*

Abstract

We present a novel, highly efficient algorithm to parallelize $O(N^2)$ direct summation method for N -body problems with individual timesteps on distributed-memory parallel machines such as Beowulf clusters. Previously known algorithms, in which all processors have complete copies of the N -body system, has the serious problem that the communication-computation ratio increases as we increase the number of processors, since the communication cost is independent of the number of processors. In the new algorithm, p processors are organized as a $\sqrt{p} \times \sqrt{p}$ two-dimensional array. Each processor has N/\sqrt{p} particles, but the data are distributed in such a way that complete system is presented if we look at any row or column consisting of \sqrt{p} processors. In this algorithm, the communication cost scales as N/\sqrt{p} , while the calculation cost scales as N^2/p . Thus, we can use a much larger number of processors without losing efficiency compared to what was practical with previously known algorithms.

PACS: 02.60.Cb;95.10.Ce; 98.10.+z

Key words: Celestial mechanics, stellar dynamics;Methods: numerical

1 Introduction

In this paper we present a novel algorithm to parallelize the direct summation method for astrophysical N -body problems, either with and without the individual timestep algorithm. The proposed algorithm works also with the Ahmad-Cohen neighbor scheme (Ahmad and Cohen 1973), or with GRAPPE special-purpose computers for N -body problems (Sugimoto et al.

1990, Makino and Taiji 1998). Our algorithm is designed to offer better scaling of the communication-computation ratio on distributed-memory multicompilers such as Beowulf PC clusters (Sterling et al. 1999) compared to traditional algorithms.

This paper will be organized as follows. In section 2 we describe the traditional algorithms to parallelize direct summation method on distributed-memory parallel computers, and the scaling of communication time and computational time as functions of the number of particles N and number of processor p . It will be shown that for previously known algorithms the calculation time scales as $O(N^2/p)$, while communication time is $O(N + \log p)$. Thus, even with infinite number of processors the total time per timestep is still $O(N)$, and we cannot use more than $O(N)$ processors without losing efficiency. $O(N)$ sounds large, but the coefficient is rather small. Thus, it was not practical to use more than 10 processors for systems with a few thousand particles, on typical Beowulf clusters.

In section 3 we describe the basic idea of our new algorithm. It will be shown that in this algorithm the communication time is $O(N/\sqrt{p} + \log p)$. Thus, we can use $O(N^2)$ processors without losing efficiency. This implies a large gain in speed for relatively small number of particles such as a few thousands. We also briefly discuss the relation between our new algorithm and the hypersystolic algorithm (Lippert et al. 1998). In short, though the ideas behind the two algorithms are very different, the actual communication patterns are quite similar, and therefore the performance is also similar for the two algorithms. Our algorithm shows a better scaling and also is much easier to extend to individual timestep and Ahmad-Cohen schemes.

In section 4 we discuss the combination of our proposed algorithm and individual timestep algorithm and the Ahmad-Cohen scheme. In section 5, we present examples of estimated performance. In section 6 we discuss the combination of our algorithm with GRAPE hardwares. In section 7 we sum up.

2 Traditional approaches

The parallelization of the direct method has been regarded simple and straightforward [see, for example, (Fox et al. 1994)]. However, it is only so if $N \gg p$ and if we use simple shared-timestep method. In this section, we first discuss the communication-calculation ratio of previously known algorithms for the shared timestep method, and then those for individual timestep algorithm with and without the Ahmad-Cohen scheme.

2.1 Shared timestep

Most of the textbooks and papers discuss the ring algorithm. Suppose we calculate the force on N particles using p processors. We connect the processors in a one dimensional ring, and distribute N particles so that each processor has N/p particles(figure 1). Here and hereafter, we assume that N is integer multiple of p , to simplify the discussion.

The ring algorithm calculates the forces on N particles in the following steps.

- (1) Each processor calculates the interactions between N/p particles within it. Calculation cost of this step is $C_f(N/p)^2/2$, where C_f is the time to calculate interaction between one pair of particles.
- (2) Each processor sends all of its particles to the same direction. Here we call that direction “right”. Thus all processors sends its particles to their right neighbors. The communication cost is $C_cN/p + C_s$, where C_c is the time to send one particle to the neighboring processor and C_s is the startup time for communication.
- (3) Each processor accumulates the force from particles they received to its own particles. Calculation cost is $C_f(N/p)^2$. If force from all particles is accumulated, go to step 5.
- (4) Each processor then sends the particles it received in the previous step to its right neighbor, and goes back to previous step.
- (5) Force calculation completed.

The time for actual calculation is given by

$$T_{f,\text{ring}} = C_f N^2/p, \quad (1)$$

and the communication time

$$T_{c,\text{ring}} = C_c N + C_s p. \quad (2)$$

The total time per one timestep of this algorithm is

$$T_{\text{ring}} = T_{f,\text{ring}} + T_{c,\text{ring}} = C_f N^2/p + C_c N + C_s p. \quad (3)$$

Here, we neglect small correction factors of order $O(1/p)$.

For fixed number of particles, the calculation cost (first term in equation 3) scales as $1/p$ while communication cost *increases*. Therefore, for large p we see the decrease in the efficiency. Here we define efficiency as

$$\eta_{\text{ring}} = T_{f,\text{ring}}/T_{\text{ring}}, \quad (4)$$

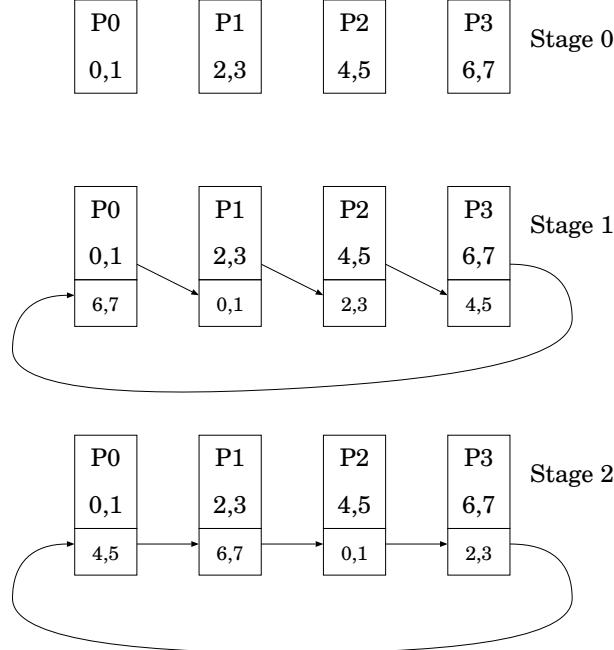


Fig. 1. The ring algorithm on 4 processors for 8 particles. In stage 0 each processor calculate the interactions between its particles. In stage 1 each processor sends its share to its right neighbor, and calculates the force from particles it received to particles it has. In stages 2 and 3 (stage 3 omitted from the figure), each processor sends what it received in the previous stage. Force calculation completes at stage 3. which reduces to

$$\eta_{\text{ring}} = \frac{1}{1 + C_c p / (C_f N) + C_s p^2 / (C_f N^2)}. \quad (5)$$

Thus, to achieve the efficiency better than 50%, the number of processor p must be smaller than

$$p_{\text{half,ring}} = \frac{N}{2C_s} (\sqrt{C_c^2 + 4C_s C_f} - C_c). \quad (6)$$

Equation (6) can be simplified in the two limiting cases

$$p_{\text{half,ring}} \sim \begin{cases} NC_f/C_c & (C_c^2 \gg C_s C_f) \\ N\sqrt{C_f/C_s} & (C_c^2 \ll C_s C_f) \end{cases} \quad (7)$$

In most of distributed-memory multicomputers, $C_c \gg C_f$. For example, with a 1 Gflops processor, we have $C_f \sim 3 \times 10^{-8}$ sec. If this processor is connected to other processor with the communication link of the effective speed of 10MB/s, $C_c \sim 3 \times 10^{-6}$ sec. The value of C_s varies depending on both networking hardware and software. Table 1 gives the order-of-magnitude values for these coefficients for several platforms.

Table 1
Time coefficients in seconds

Network	C_f	C_s	C_c	$\sqrt{C_f/C_s}$	C_f/C_c
Fast Ethernet	3×10^{-8}	10^{-4}	3×10^{-6}	0.017	0.01
Gigabit Ethernet	3×10^{-8}	10^{-4}	3×10^{-7}	0.017	0.1
Myrinet	3×10^{-8}	10^{-5}	3×10^{-7}	0.05	0.1

With the Fast Ethernet, $p_{\text{half,ring}}$ is $N/100$. Faster networks help to increase $p_{\text{half,ring}}$, but we can see that even with a very low-latency network system like Myrinet, $p_{\text{half,ring}}$ is latency-limited. Fast, high-latency network such as Gigabit Ethernet does not offer much improvement over Fast Ethernet.

A possible alternative of the ring algorithm is the copy algorithm (figure 2), in which all processors have complete copy of the system at the beginning of the timestep. Then, each processor calculates the forces on its share of N/p particles, and integrates their orbits. After the orbit integration is done, the updated particles in each processor must be broadcasted to all other processors. If we use a simple ring algorithm to broadcast the data, the scaling characteristic of this algorithm is exactly the same as that of the ring algorithm.

If the communication network has the connectivity better than 1-D ring, we can use the so-called message-combining technique, which is essentially the same algorithm as what is used for global summation. Assume that we have 2^s processors with fully connected network. At the first stage, each processor sends its data to its right neighbor. At the second stage, each processor sends both its original data and the data it received at the first stage to its second right neighbor, and in the third stage to fourth neighbor. In this way, all processors receive the data of all other processors after $s = \log_2 p$ stages. Note that the amount of the data received is the same as the ring algorithm. Only the startup overhead is reduced. With this implementation of the copy algorithm, the total time becomes

$$T_{\text{copy}} = T_{f,\text{ring}} + T_{c,\text{ring}} = C_f N^2/p + C_c N + C_s \log_2 p. \quad (8)$$

In this case, we can almost always ignore the contribution of the last term, and the number of processors with 50% efficiency is given by

$$p_{\text{half,copy}} \sim NC_f/C_c. \quad (9)$$

Thus, we can use a larger number of processors, as far as the memory of individual node is large enough to keep the copy of the complete system. We could also implement some hybrid of the ring and copy algorithm to reduce the memory requirement.

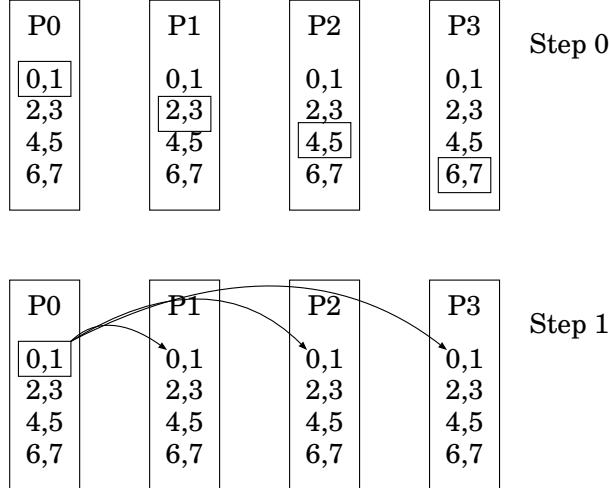


Fig. 2. The copy algorithm on 4 processors for 8 particles. In stage 0 each processor calculates the forces on its share of particles and integrates their orbits. In stage 1, processor 0 broadcasts its share of particles to all other processors. In the following stages (not shown in the figure), each processor broadcasts its share in turn.

2.2 Individual timestep

Here, what we actually consider is the so-called blockstep method (McMillan 1986, Makino 1991), where we organize the timesteps of particles so that the number of particles share exactly the same time becomes maximum. This is clearly desirable to achieve high efficiency on parallel computers. We denote the average number of particles which share the same time as n . According to a simple theoretical estimate, $n \propto N^{2/3}$ if the central density of the system is not very high (Makino 1991).

It's not easy to extend the ring algorithm so that it can handle the block-step algorithm. A naive approach is just to pass around all particles in the system in the same way as in the case of the shared timestep. In this case, calculation cost is $C_f N n / p$ while communication cost is $C_c N$. Thus, relatively speaking communication becomes more expensive by a factor of N/n , which is essentially the gain of calculation speed by the individual timestep algorithm.

The copy algorithm is much easier to extend to the blockstep method. At each blockstep, each processor determines which particles it will update, so that it updates n/p particles which are not overlapped with particles updated by other processors. Then they calculate the forces on them and integrate their orbits. At the end of the timestep, they broadcast the updated particles. The calculation cost is $C_f N n / p$, while the communication cost is $C_c n + C_s \log_2 p$. Thus, the communication is reduced by the same factor as that for the calculation cost.

Note, however, that the effect of the startup overhead of communication is increased. We can still ignore the startup time if

$$\log_2 pC_s < C_c n, \quad (10)$$

which is okay except for the case of the Gigabit ethernet. Thus, individual timestep does not change the scalability of the algorithm.

We cannot easily use more than n processors, since each processor should have at least one particles to integrate. At least under the assumption of $n = N^{2/3}$, $p_{\text{half, copy}}$ becomes larger than n for $N > 1000$, for the case of Myrinet. In this case, we can distribute the work to calculate the force on one particle to several processors. This of course increases the communication cost, but the increase is around $C_c p/n$ which is always smaller than $C_c n$.

In theory, it is possible to extend the ring algorithm in the following way. Instead of passing around the particles which exert the forces, we can pass around the particles which receives the force. In this way, the ring algorithm can achieve the same scaling as the copy algorithm. The naive use of the ring communication pattern again incurs the high startup cost. So it is necessary to use the message combining technique.

The ring algorithm suffers a potential load imbalance problem, since particles are assigned to fixed processors. At any given blockstep, there is no guarantee that the number of particles to be integrated is balanced. Of course, we can try to migrate particles with small timestep from heavily loaded processors to lightly loaded processors, and vice versa, to reduce the imbalance. The effectiveness of such an algorithm is an open question, though we expect the load balancing would probably work fine.

For the individual timestep method, however, there is no reason to prefer the (modified) ring algorithm over the copy algorithm, since the efficiency of the ring algorithm at the best only matches that of the copy algorithm. The potential advantage of the ring algorithm is that it requires less memory, since the particles are distributed over processors. However, since the number of particles we consider here is relatively small, the memory requirement is not very important.

2.3 The Ahmad-Cohen scheme

The copy algorithm is problematic to extend to the Ahmad-Cohen scheme. The problem is that informations to be passed around increases since now each particle has its own neighbor list. This list must be communicated to all

processors. On the other hand, the calculation cost is further reduced.

The ring algorithm is better than the copy algorithm here, since with the ring algorithm we do not have to pass around the neighbor list. Each processor maintains partial neighbor lists for all particles, which contains only the particles on that processor. The scaling relation of calculation and communication costs are essentially the same as that of the individual timestep, except that now total number of particles N is replaced with average number of force calculations per timestep. Theoretically, it is of the order of $N^{3/4}$ (Makino and Hut 1988). This means we can now use only $N^{3/4}C_f/C_c$ processors. Even with Myrinet, this number is rather small. For example, we can use only 100 processors for $N = 10^4$.

2.4 Summary

We overviewed known algorithms to parallelize the direct force calculation. All algorithms share the same problem that the relative cost of the communication goes up as we increase the number of processors. More troublesome is that even for fixed N and p , the relative cost of communication is higher for a more advanced algorithm, resulting in the partial cancelation of the gain in the speed achieved by advanced algorithms.

We have not discussed the “hyper-systolic” algorithm (Lippert et al. 1998). We will briefly discuss them after we introduce our new algorithm in the next section.

3 The new algorithm

The problem with the traditional schemes is that each processor must receive the information of all particles updated at each timestep. This is the case for all algorithms described in the previous section. Therefore, the communication cost remains constant, while calculation cost decreases as we increase p .

If all processors keep the complete copies of the system, it is clear that they must receive all data updated by other processors at each timestep. If all processors only store their own shares, they still have to receive all updated particles to calculate forces either to or from them.

If we divide the processors to subgroups, and let the data be copied only within the subgroups, we may be able to reduce the communication cost. In the following, we’ll discuss how such subdivision works.

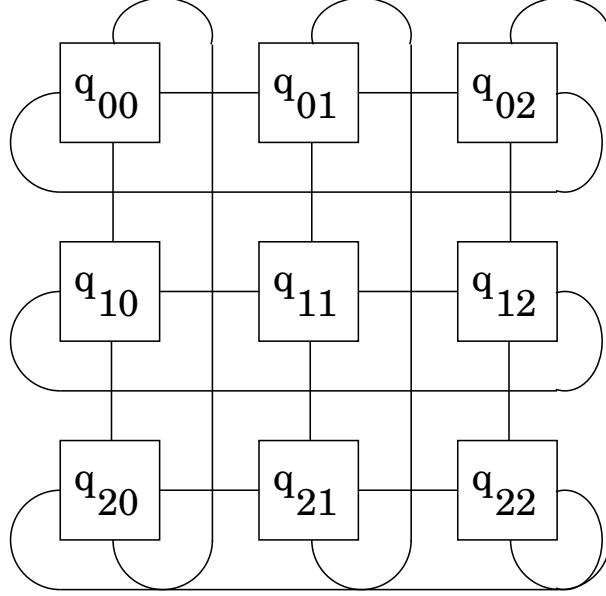


Fig. 3. Two dimensional array of processors. In this example, a torus network is shown.

Here, we assume that we have $p = r^2$ processors, where r is a positive integer, and that they are organized as $r \times r$ 2D grid (torus). Processors are numbered as $q_{0,0}$ to $q_{r-1,r-1}$. It is easy to extend the new algorithm to any rectangular grid with the geometry of $r \times kr$, where k is a positive integer. Such configuration can reduce the memory requirement, but increases the communication cost. Therefore we do not discuss such non-square grids in this paper.

We divide N particles to r subsets each with N/r particles, and let processors $q_{x,i}$ (here x, i means any index pair with column address i) to have i -th subset. Thus, processors $q_{0,0}$ through $q_{r,0}$ have the same data of zeroth group.

The force calculation can be done by the following two steps. First, we apply the ring algorithm for each row. However, instead of sending all particles in each processor, they send only N/r^2 particles. To do so, within processors in the same column the particles are further subdivided to r sub-subgroups.

After one rotation of the ring is finished, each processor obtained the partial force from N/r particles in the ring (row) to N/r particles in the column. Calculation cost of this stage is $C_f N^2/p$ and communication cost is $C_c N/r + C_s r$, since we send N/r^2 particles r times.

In the second stage, we simply take the summation of r partial forces for each particles, which are distributed on the r processors in the same column. The total force is obtained on one processor, which then broadcasts them to all other processors in the same column. The communication cost depends very much on the connectivity of the network. In the worst case of 1-D network, the communication cost of this stage is $C_c N$. The summation takes r steps in 1-D

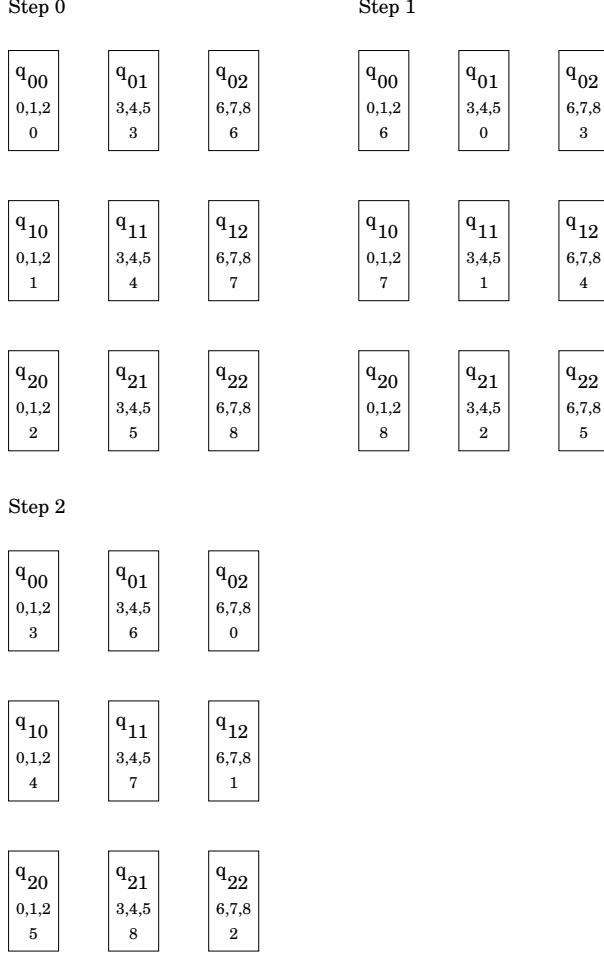


Fig. 4. The 2D ring algorithm.

ring, and each processor has to send N/r data. Of course, if we can overlap calculation and communication, the scaling can be $2C_cN/r + C_s r$, which is far more preferable. With full crossbar networks in this column direction, the communication cost becomes $2C_cN \log_2 r/r + 2C_s \log_2 r$, assuming that we cannot overlap communication and calculation. If we can overlap them, the communication cost is reduced to $2C_cN/r + 2C_s \log_2 r$. In the following, for simplicity we assume that the communication cost of this stage is the same as that for the first stage.

The total time per one timestep of this algorithm is

$$T_{\text{2Dring}} = T_{\text{f,2Dring}} + T_{\text{c,2Dring}} = C_f N^2/r^2 + 2(C_c N/r + C_s r). \quad (11)$$

For the number of processors $p = r^2$ for which the efficiency is 50%, we have a cubic equation. For the two limiting cases, the solution is given as

$$P_{\text{half,2Dring}} \sim \begin{cases} (NC_f/C_c)^2 & (N < N_{\text{c,2Dring}}), \\ N^2(C_f/C_s)^{2/3} & (N > N_{\text{c,2Dring}}), \end{cases} \quad (12)$$

Table 2

Critical values of N for different algorithms

Network	$N_{c,2\text{Dring}}$	$N_{c,2\text{Dbcast}}$	$N_{c,\text{ind},2\text{D}}$
Fast Ethernet	300	3×10^5	900
Gigabit Ethernet	0.3	90	200
Myrinet	3	60	70

where $N_{c,2\text{Dring}}$ is defined as

$$N_{c,2\text{Dring}} = \frac{C_c^3}{C_f^2 C_s} \quad (13)$$

The values of $N_{c,2\text{Dring}}$ for typical networks are given in table 2. Clearly, N is almost always larger than $N_{c,2\text{Dring}}$. This means that the total performance is limited by the latency of the network.

Even so, the number of processors we can use with this 2D algorithm is significantly larger than that for 1D ring, for any value of N . If $N < N_c$, we can use $O(N^2)$ processors. Even if $N > N_{c,2\text{Dring}}$, we can still use $O(N^{4/3})$ processors.

In this 2D ring algorithm, the $O(r)$ term in the communication cost limits the total performance. We can reduce this term by using the extension of the copy algorithm to 2D.

Instead of using the ring algorithm in the first stage, processors q_{ii} broadcast their data to all other processors in the same row. After this broadcast processor q_{ij} has both group i and group j . Then each processor calculates the force on particles they received (group i) from particles they originally have (group j). In this scheme, the communication cost is reduced to $NC_c/r + C_s$ if the network switch supports the broadcast. If the network does not support the broadcast, the cost varies between $C_c N/r + C_s r$ for the case of a ring network and $C_c N/r + C_s \log_2 r$ for a full crossbar.

In the second stage, summation is now taken over the processors in the same row. Here, result for row i must be obtained on processor q_{ii} , which then broadcasts the forces to all processors in the same column. After this broadcast, all processors have the forces on all particles in them. They can then use this forces to integrate the orbits of particles.

In this algorithm, the time integration calculation is duplicated over r processors in the same column, but in most cases this does not matter. One alternative is that processor q_{ii} performs the time integration and broadcasts the updated data of particles to other processor in the same column. Yet another possibility is to let each of r processor to integrate N/r^2 particles, which

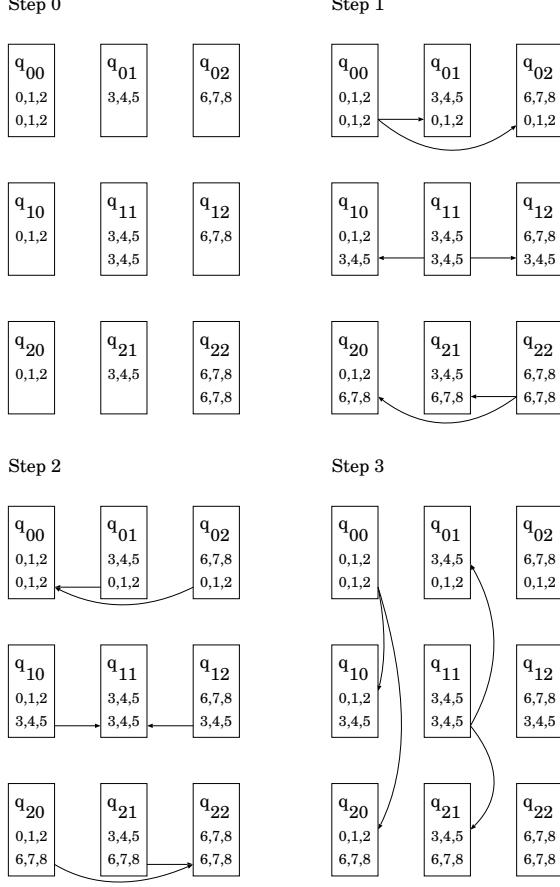


Fig. 5. The 2D broadcast algorithm.

each of them then broadcasts within the column. Which approach is the best depends on the ratio between calculation speed, communication speed and communication startup overhead.

The total time per one timestep of this algorithm is

$$T_{\text{2Dbcast}} = T_{\text{f,2Dbcast}} + T_{\text{c,2Dbcast}} = C_f N^2 / r^2 + 2(C_c N / r + C_s \log_2 r). \quad (14)$$

For the number of processors $p = r^2$ for which the efficiency is 50%, we have a cubic equation. For the two limiting cases, the solution is given as

$$p_{\text{half,2Dbcast}} \sim \begin{cases} (NC_f/2C_c)^2 & (N < N_{\text{c,2Dbcast}}), \\ N^2 C_f / [C_s \log 2 \cdot (N^2 C_f / 2C_s)] & (N > N_{\text{c,2Dbcast}}), \end{cases} \quad (15)$$

where $N_{\text{c,2Dbcast}}$ is defined as

$$N_{\text{c,2Dbcast}} = \sqrt{\frac{C_s}{C_f}} \exp \left(\log_2 \frac{2C_c^2}{C_f C_s} \right). \quad (16)$$

The critical value of N , $N_{c,2\text{Dbcast}}$, is larger than that for the 2D ring version of the algorithm. This is because we reduced the $C_s r$ term in the communication cost to $C_s \log r$. More importantly, even for $N > N_{c,2\text{Dbcast}}$, p_{half} is only logarithmically smaller than $O(N^2)$. Thus, with this broadcast version of the algorithm we can really use $O(N^2)$ processors and still achieve high efficiency.

3.1 Relation with the hyper-systolic algorithm

Now the relation between our algorithm and the hyper-systolic algorithm (Lippert et al. 1998) must be obvious. The “regular bases” version of the hyper-systolic algorithm applied to r^2 processors works in the essentially the same way as the ring version of our algorithm works, though in order to derive our algorithm we do not need to use any complex concepts like h -range problem or Additive Number Theory. To put things in a slightly different way, the hyper-systolic algorithm is a complex way to reconstruct combination of rowwize ring and columwize summation on a 2D network by a sequence of shift operations in 1-D ring network.

Thus, as far as the $C_s r$ term is small, our algorithm and the hyper-systolic algorithm show the same scaling. However, since $C_s r$ term would almost always limit the scaling, the broadcast version of our algorithm is almost always better than the hyper-systolic algorithm. In addition, our algorithm is by far easier to understand and implement.

This simplicity of our algorithm makes it possible to extend our algorithm to the individual timestep scheme and even to the Ahmad-Cohen scheme, which will be discussed in the following sections.

4 Application to Individual timestep

4.1 Standard individual timestep

If we use the broadcast version as the base, the extension to the individual timestep method is trivial. Instead of broadcasting all particles in the first stage, we broadcast only the particles in the current block. In the following steps, we always send only data related with the particles in the current block. Everything else is the same as in the case of the shared timestep algorithm. Using the same assumption of $n \sim N^{2/3}$, we have

$$T_{\text{ind},2\text{D}} = C_f N^{5/3} / r^2 + 2(C_c N^{2/3} / r + C_s \log_2 r), \quad (17)$$

and

$$p_{\text{half,ind},2D} \sim \begin{cases} (NC_f/2C_c)^2 & (N < N_{c,\text{ind},2D}), \\ N^{5/3}C_f/C_s \log_2(N^{5/3}C_f/2C_s) & (N > N_{c,\text{ind},2D}), \end{cases} \quad (18)$$

where $N_{c,\text{ind},2D}$ is now given by the following implicit equation

$$N_{c,\text{ind},2D}^{1/3} \log_2 \left(\frac{N_{c,\text{ind},2D}^{5/3} C_f}{2C_s} \right) = \frac{4C_c^2}{C_f C_s}. \quad (19)$$

For the example values in table 1, the value of $N_{c,\text{ind},2D}$ is fairly small. So we can use only $O(N^{5/3})$ processors. However, this is still much larger than the number of processors that can be used with 1D implementation of the individual timestep algorithm.

The same load-balance problem as we have discussed in the case of the copy algorithm occurs with this method. We need some load-balancing strategy to actually use this method.

4.2 Application to the Ahmad-Cohen scheme

The difference from the individual timestep scheme is that the neighbor list is created/used to calculate the forces. the neighbor list for forces from particles in group j to particles in group i is created, stored and used only by processor q_{ij} . Therefore, there is no increase in the communication cost, except for the summation of the number of neighbors. The total calculation time and the 50% efficiency processor count are given by:

$$T_{AC,2D} = C_f N^{17/12}/r^2 + 2(C_c N^{2/3}/r + C_s \log_2 r), \quad (20)$$

and

$$p_{\text{half,AC},2D} \sim \begin{cases} N^{3/2}(C_f/2C_c)^2 & (N < N_{c,AC,2D}), \\ N^{17/12}C_f/C_s \log_2(N^{17/12}C_f/2C_s) & (N > N_{c,AC,2D}), \end{cases} \quad (21)$$

where $N_{c,AC,2D}$ is now given by the following implicit equation

$$N_{c,AC,2D}^{1/12} \log_2 \left(\frac{N_{c,AC,2D}^{17/12} C_f}{2C_s} \right) = \frac{8C_c^2}{C_f C_s}. \quad (22)$$

Note that, in this case, whether or not $N > N_{c,AC,2D}$ makes very small difference for the number of processors, since the difference is only of the order

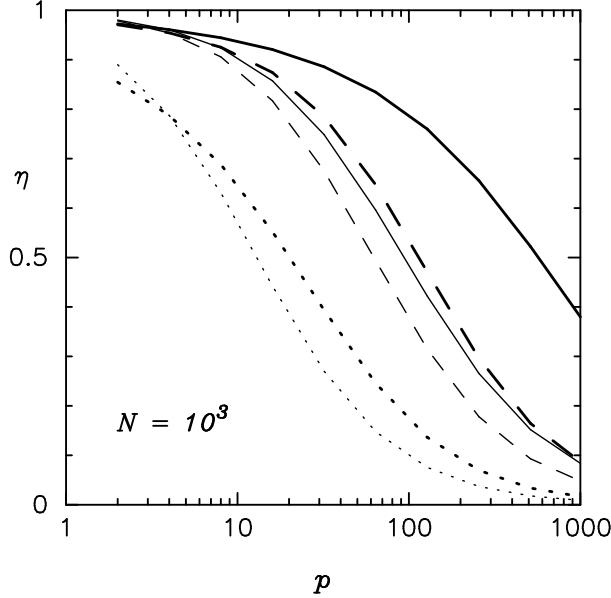


Fig. 6. Efficiencies of various algorithms discussed in the text. Thin curves correspond to 1D algorithms and thick curves to 2D algorithms. Solid, dashed and dotted curves represent shared timestep, individual timestep and Ahmad-Cohen scheme, respectively. Number of particles is 10^3 and a Myrinet-like network is assumed.

of $(N/N_{c,AC,2D})^{1/12}$. Thus, practically we can say that we can use $O(N^{3/2})$ processors with the 2D version of the Ahmad-Cohen scheme.

5 Comparison of traditional and proposed algorithms

In this section, we present the theoretical comparison of the proposed algorithm and the traditional one-dimensional algorithm. First we show the result for the case of Myrinet-like fast network.

Figures 6 to 8 show the efficiencies for three different values of N as the function of the number of processors p . It is clear that 2D algorithms allow us to use much larger number of processors compared to their 1D counterparts. The gain is larger for larger N , but becomes smaller as we use more advanced algorithms. The gain for individual timestep is smaller than that for shared timestep, and that for the Ahmad-Cohen scheme is even smaller.

Even so, the gain in the processor count is more than a factor of 5, for the case of the Ahmad-Cohen scheme and $N = 10^4$. We believe this is quite a large gain in the parallel efficiency.

Figure 9 shows the efficiencies for the case of the Fast Ethernet. With the 2D algorithm we can use more than 500 processors even with Ahmad Co-

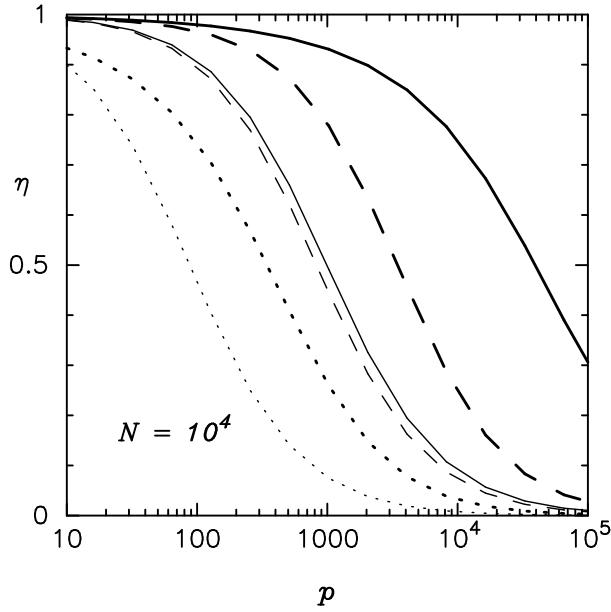


Fig. 7. Same as figure 6 but for $N = 10^4$.

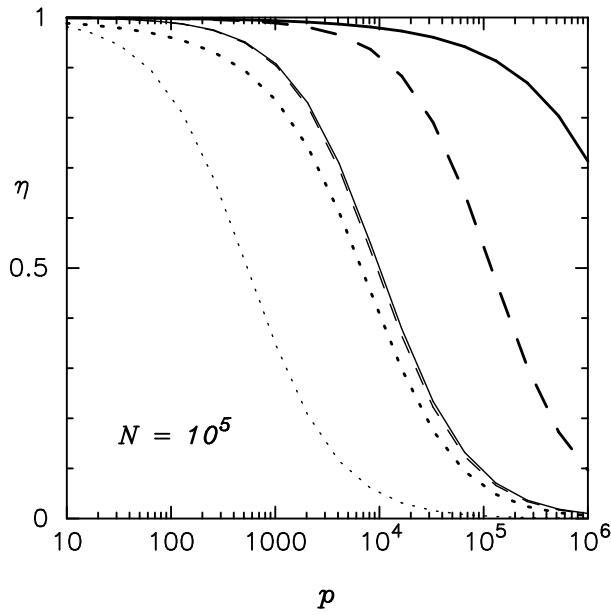


Fig. 8. Same as figure 6 but for $N = 10^5$.

hen scheme, for $N = 10^5$. PC clusters with inexpensive networks seem to be very attractive platforms to implement parallel version of the Ahmad-Cohen scheme.

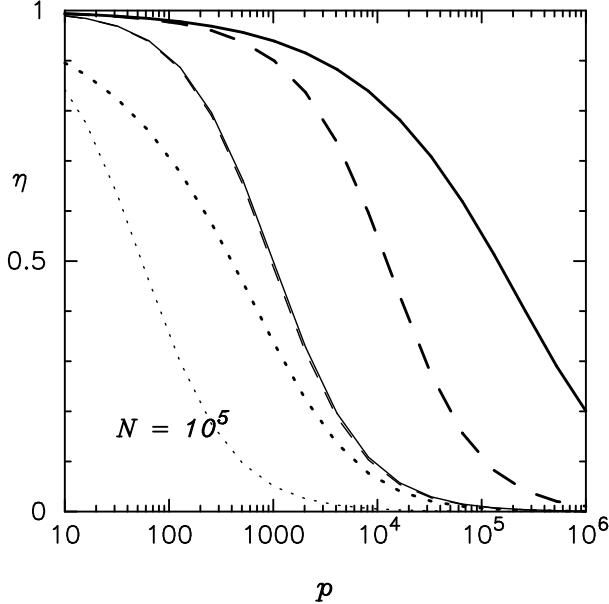


Fig. 9. Same as figure 8 but for Fast Ethernet.

6 Combination with GRAPE

The only thing GRAPE does is to greatly reduce the value of C_f . Thus, the same 2D network of processors each with one GRAPE processor works fine, if the cost of the frontend is less than that of a GRAPE processor.

GRAPE-6 achieves essentially the same effect as this 2D processor grid, but using only r hosts and r^2 GRAPE processors connected with a rather elaborate multistage networks. In hindsight, such an elaborate network is unnecessary, if the fast network is available for a low cost.

From the point of view of the scaling relations, what a GRAPE hardware changes is simply C_f . If we attach a 1Tflops GRAPE hardware to a 1 Gflops host, we reduce C_f by a factor of 10^3 . This means that the limiting factor for the number of processors is almost always C_c and not C_s . Thus, for a parallel GRAPE system, high-throughput, high-latency network such as Gigabit Ethernet is a practical choice.

Figures 10 and 11 shows the efficiencies for GRAPE-6 system. Since C_f is much smaller, the number of processors we can use becomes much smaller. Of course, in the case of 1D algorithms, the actual speed we can achieve does not depend on C_f , since the total speed is p/C_f and p_{half} is proportional to C_f . Figure 11 indicates that we can achieve the speed of multiple petaflops with currently available technology, by configuring several thousand GRAPE-6 boards into a 2D network.

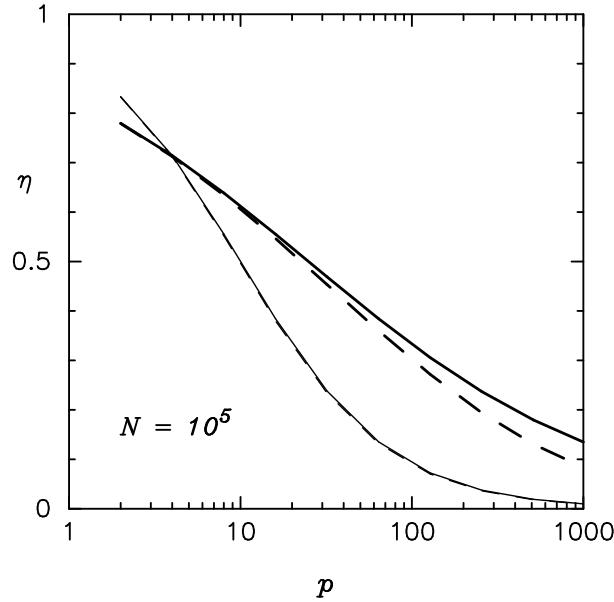


Fig. 10. Same as figure 8 but for $C_f = 3 \times 10^{-11}$.

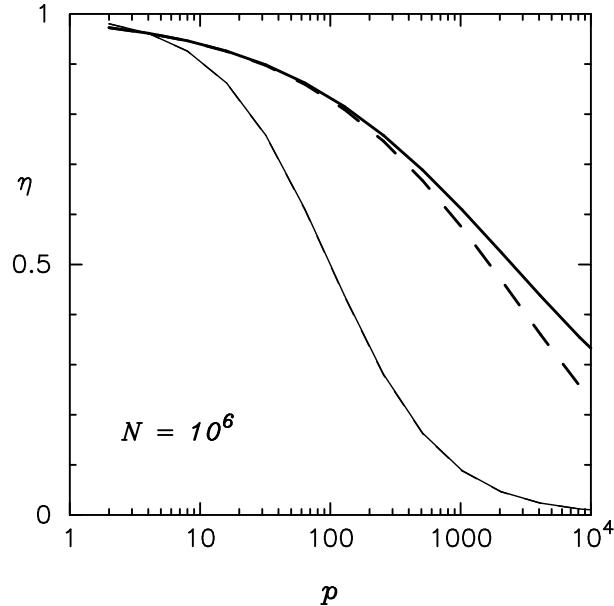


Fig. 11. Same as figure 10 but for $N = 10^6$.

7 Summary

We described a new two-dimensional algorithm to implement the direct summation method on distributed-memory parallel computers. The basic idea of the new algorithm is to organize processors to $r \times r$ 2D network, and let the data be shared both rowwize and columnwize. In this way, we can reduce the communication cost from $O(N)$ of the previously known algorithms to $O(N/r)$.

For the case of the shared timestep algorithm, the new algorithm behaves in essentially the same as the “regular bases” version of the hyper-systolic algorithm does. However, with the broadcast version of our algorithm the communication overhead is reduced, which resulted in the better scaling. Also, our algorithm is much simpler, which helped us to extend our algorithm to individual timestep and the Ahmad-Cohen scheme, as well as combination with GRAPE hardwares.

For all cases, compared to the previously known algorithm, the number of processors we can use without losing efficiency is almost *squared*. This is a quite large improvement in the efficiency of a parallel algorithm.

Usually, a paper which proposes a new parallel algorithm should offer the verification of the concept, by means of the timing measurement of actual implementation. In this paper we omit this verification, because we believe it’s important to let those who working on hyper-systolic algorithms be aware of simpler alternatives.

In this paper, we assumed a network with full connectivity. This assumption is okay with small PC clusters, but not true on large MPPs. In this case, parallel efficiency of 1D algorithm is significantly reduced, and relative gain of 2D algorithm would become much larger.

Acknowledgments

I thank Rainer Spurzem and Yoko Funato for valuable discussions. This work is supported in part by the Research for the Future Program of Japan Society for the Promotion of Science (JSPS-RFTP97P01102).

References

- Ahmad, A. & Cohen, L., 1973, Journal of Computational Physics, 12, 389
- Fox, G. C., Williams, R. D., & Messina, P. C., 1994, Parallel Computing Works!, Morgan Kaufmann, San Francisco.
- Lippert, T., Seyfried, A., Bode, A., & Schilling, K., 1998, IEEE Transactions on Parallel and Distributed Systems, 9, 97
- Makino, J. & Hut, P., 1988, ApJS, 68, 833
- Makino, J. & Taiji, M., 1988, Scientific Simulations with Special-Purpose Computers — The GRAPE Systems, John Wiley and Sons, Chichester.

Makino, J., 1991, PASJ, 43, 859

McMillan, S. L. W., 1986, The vectorization of small-n integrators, in edited by P. Hut & S. McMillan (Eds), The Use of Supercomputers in Stellar Dynamics, Springer, New York, pp. 156–161.

Sterling, T. L., Salmon, J., Becker, D. J., & Savarese, D. F., 1999, How to Build a Beowulf: A Guide to Implementation and Application of PC Clusters, MIT Press, Cambridge.

Sugimoto, D., Chikada, Y., Makino, J., Ito, T., Ebisuzaki, T., & Umemura, M., 1990, Nature, 345, 33